Georgia State University

ScholarWorks @ Georgia State University

Public Health Theses

School of Public Health

Spring 5-11-2018

Student Risk Screening Scale for Internalizing and Externalizing Behaviors (SRSS-IE): Examining the Predictive Validity using Office Discipline Referral Data

Camara Gregory

ABSTRACT

Student Risk Screening Scale for Internalizing and Externalizing Behaviors (SRSS-IE): Examining the Predictive Validity using Office Discipline Referral Data

By

CAMARA JANAE GREGORY

May 11, 2018

Despite advances in public awareness of mental disorders in youth, there is still a significant issue of under identification of students that may need mental health services. Schools have become the most common setting for children to receive mental health services and can serve as an entry point for screening and provision of services. Universal mental health screening is a systematic, quick and inexpensive method for identifying students who may benefit from mental health services. Currently, schools rely on office discipline referral data or suspension data to identify students who may need additional social/emotional/behavioral support. These discipline data may be effective at identifying students with externalizing behaviors but there is concern that students who internalize their frustration may not incur a discipline infraction and therefore may "fall through the cracks," or not receive needed supports. This study explores whether a universal screener for mental health identifies students at risk for mental health concerns who may not be identified through school office discipline referral data. In other words, do scores from a mental health screener predict office discipline referrals (ODR). The Student Risk Screening Scale, Internalizing/Externalizing (SRSS-IE) was administered to 1,201 elementary students in 3 elementary schools. ODR data for those students were matched to the SRSS-IE data. Results showed the externalizing scale to be predective of year-end ODRs with higher total scores being associated with more ODRs. However, the internalizing scale was found to negatively predict ODRs, in other words students with internalizing behaviors were likely to receive fewer or no ODRs. This data provides support for the use of screener data in schools to predict and prevent problem behaviors opposed to relying solely on the use of more reactive data such as ODRs. Relying on ODR data alone for data-based decision making in school, may be ineffective as it may not capture students with internalizing behaviors.

Keywords: Student Risk Screening Scale – Internalizing/ Externalizing, office disciple referrals, universal screening, predictive validity, nonparametric analyses

Student Risk Screening Scale for Internalizing and Externalizing Behaviors (SRSS-IE): Examining the Predictive Validity using Office Discipline Referral Data

by

CAMARA JANAE GREGORY

MPH candidate, GEORGIA STATE UNIVERSITY

B.S., UNIVERSITY OF WISCONSIN – MADISON

A Thesis Submitted to the Graduate Faculty
of Georgia State University in Partial Fulfillment
of the
Requirements for the Degree

MASTER OF PUBLIC HEALTH

ATLANTA, GEORGIA
30303

APPROVAL PAGE

Student Risk Screening Scale for Internalizing and Externalizing Behaviors (SRSS-IE):
Examining the Predictive Validity using Office Discipline Referral Data

by

CAMARA JANAE GREGORY

Approved:

Dr. Brian Barger
Committee Chair

Dr. Emily Graybill
Committee Member

Dr. Andrew Roach
Committee Member

May 11, 2018

Author's Statement Page

In presenting this thesis as a partial fulfillment of the requirements for an advanced degree from Georgia State University, I agree that the Library of the University shall make it available for inspection and circulation in accordance with its regulations governing materials of this type. I agree that permission to quote from, to copy from, or to publish this thesis may be granted by the author or, in his/her absence, by the professor under whose direction it was written, or in his/her absence, by the Associate Dean, School of Public Health. Such quoting, copying, or publishing must be solely for scholarly purposes and will not involve potential financial gain. It is understood that any copying from or publication of this dissertation which involves potential financial gain will not be allowed without written permission of the author.

Camara Janae Gregory, Author

TABLE OF CONTENTS

List of Tables……………………………………….…………………………………...........iv
List of Figures………………………………………………………………………………v
Introduction and Literature Review 1
1.1 Universal Screening for Mental Health in Schools ………………………….……….…..... 1
1.2 Student Risk Screening Scale…………………………….……………………………..………4
1.3 Student Risk Screening Scale – Internalizing/Externalizing……………………...………5
1.4 Identifying Problem Behaviors in Schools….……………………………………………6
1.5 Office Discipline Referrals………………………………………………………………7
1.6 Rationale for Current Study………………………………………………………………9
1.7 Research Questions………………………………………………………………………9

METHODS AND PROCEDURES………………….. 10
2.1 Context……………………………………………………………………………….10
2.2 Participants ad Settings………………………………………………………………….10
2.3 Procedures…………………….………………………………………………………10
2.4 Measures………...11
2.5 Statistical Analysis..13

RESULTS..16

DISCUSSION AND CONCLUSION... 19
4.1 Limitations...22
4.2 Future Research and Implications...22

REFERENCES...28

List of Tables

Table 1: County M Descriptive Statistics……………………………………………………………24

Table 2: Bivariate analyses for SRSS-IE Scale Scores and ODR Totals………………………25

Table 3: Intercorrelations among ODRs and SRSS-IE Scales…………….……………………….26

Table 4: Results of Poisson Model Selection………………………………………………….26

Table 5: Cronbach's Coefficient Alphas…………………………………………………….…26

List of Figures

Figure 1: Student Risk Screening Scale – Internalizing/ Externalizing (SRSS-IE12) ……………27

CHAPTER 1

INTRODUCTION & LITERATURE REVIEW

According to the National Comorbidity Survey Adolescent Supplement (NCS-A), approximately 1 and 4 or 5 children meet the criteria for a clinical identification of a mental health disorder (Merikangas, 2010), and less than half of these youth receive the services that they need (Ballinger, 2016). Mental health issues can negatively impact the developmental and academic trajectory of children (Ballinger, 2016). Data suggest that the onset of mental health problems during elementary school, more specifically behavioral and emotional difficulties, is associated with increased risk for future aggressive behavior, academic failure, and an increased risk for suspension, dropout, and involvement in the juvenile justice system (Bradshaw, 2008; Ballinger, 2016). It is essential that universal early identification systems be established to help route children with mental health concerns to appropriate services to help reduce the larger impact these conditions could have for affected children and their communities (Jones et al., 2002; Burns, et al., 2016). According to The White House (2013), schools may be helpful in ensuring children receive necessary treatment for mental health problems by providing sources of early identification, referral for treatment, training for school staff on early identification, and response to mental health training.

1.1 Universal Screening for Mental Health in Schools

Universal mental health screening in schools is one process by which educators seek to identify mental health problems in children and is recommended as the best initial step to identify and intervene with at-risk students (Ballinger,2016). Universal screening is the systematic assessment of all children within a given class, school building, or school district, on social-emotional indicators that the school personnel and community have agreed are important

(Ikeda, Neessen, & Witt, 2008). Universal screening is a quick, inexpensive approach to identify students that may be at-risk for developing behavior and emotional difficulties (Renshaw et al, 2009). Like academic screeners, social/emotional screeners are not used to make a diagnosis, but rather provide information for those who may be at risk for developing behavioral or emotional difficulties (Chafouleas, Volpe, Gresham, & Cook, 2010). Within systems without universal mental health screenings, students are typically referred for services only when their behavior reaches extreme disruption of instruction in the classroom (Kim, Furlong Dowdy & Felix, 2014). While many students with mental health concerns communicate their frustration through disruptive classroom behavior, other students with mental health concerns do not necessarily present with observable concerning behaviors and may internalize their frustration (Bradshaw, Buckley, Ialongo, 2008). Students at risk for behavior problems include both students with externalizing and internalizing behaviors (Lane, Oakes, Cantwell, Schatschneider, Menzies, Crittenden, & Messenger, 2016). Students with externalizing concerns present with outward directed behaviors such as verbal and physical aggression (Bradshaw, 2008). These behaviors tend to disrupt instruction, and thus are quickly identified by teachers, even without systematic screening efforts (Lane, Menzies, Oakes, Lambert, Cox & Hankins, 2012). Alternatively, students with internalizing behaviors often present with inward directed behaviors such as symptoms of anxiety, depression, social withdrawal, and even self-inflicted pain, and often go unnoticed by the adults in their environment (Bradshaw, 2008). Bradshaw et al. (2008) found children with externalizing behaviors were more likely to be detected by school staff and receive mental health services, compared to students with internalizing behaviors. Overall, the likelihood of receiving services remained low throughout elementary and increased substantially once children transitioned to middle school (Bradshaw, 2008). Proactive and accurate identification of students at risk for mental health concerns is dependent on the availability of psychometrically strong behavior screening tools (Glover & Albers, 2007). Given the critical nature of prevention and early identification of students at-risk, there is a clear need for feasible and reliable screening tools (Glover & Albers, 2007).

Oakes and colleagues recently reviewed six available behavior screening tools: Systematic Screening for Behavior Disorders (SSBD; Walker & Severson,1992), the Early Screening Project (ESP; Walker, Severson, & Feil, 1995), the Student Risk Screening Scale (SRSS; Drummond, 1994), the Strengths and Difficulties Questionnaire (SDQ; Goodman, 1997), the BASC-2 Behavioral and Emotional Screening System (BASC-2 BESS; Reynolds & Kamphaus, 2007), and the Social Skills Improvement System - Performance Screening Guide (SSIS-PSG) (Oakes, Lane, Cox &Messenger, 2014). These tools range from multiple-gating procedures, to self-report and teacher-report measures completed two to three times in a school year. The screening tools range from a start-up cost of US$130 with US$1 added for each additional form (BASC-2 BESS; Reynolds & Kamphaus, 2007), US$200 for reproducible materials (SSBD), to free access (SRSS). Some tools do not require scoring software, while others have tools available for purchase. While many of these tools are evidence-based (Oakes, Lane, Cox &Messenger, 2014), they have several weaknesses, including the cost and time needed to complete individual ratings for multiple students (McIntosh, Campbell, Carter & Zumbo, 2009). This highlights a need for inexpensive, reliable screening tools that can be used continuously in multiple screening waves. Public schools in particular need these resources to identify students in need of additional supports.

1.2 Student Risk Screening Scale

The Student Risk Screening Scale (SRSS; Drummond, 1994) is an open-access systematic screener initially designed to identify students at risk for antisocial behavior patterns in elementary school utilizing seven behavioral indicators: (a) steal; (b) lie, cheat, sneak; (c) behavior problem; (d) peer rejection; (e) low academic achievement; (f) negative attitude; and (g) aggressive behavior. Taking about 10 minutes of their time, teachers rate their entire class on a zero to three Likert scale: 0=never, 1=occasionally; 2=sometimes; and 3=frequently on each item. Completion results in a sum representing the level of risk for each student, as developed by Drummond (1994). Scores range from zero to 21 with three specific risk categories based on these sums: low- (0-3), moderate- (4-8), and high- (9-21) risk. The SRSS's brevity, reliability, and free access makes it a practical tool for continued school use. Over the last ten years many studies have documented the reliability of the SRSS for use in elementary (Flannery, Fenning, MnIntosh, 2014), middle (Lane, Parks, Kalberg & Carter, 2007; Lane, 2010) and high schools. The SRSS has strong psychometric properties: internal consistency, test-retest reliability, convergent validity with other screeners, and predictive validity (Flannery, Fenning, MnIntosh, 2014; Lane, Parks, Kalberg & Carter, 2007; Lane, 2010; Drummond,1994). A series of studies conducted at the elementary level (Lane, Little, Casey, Lambert, Wehby, Weisenbach & Phillips, 2009; Lane, Kalberg, Lambert, Crnobori & Bruhn, 2010) examined the psychometric rigor of the SRSS relative to the SSBD, a commonly used tool for screening for externalizing and internalizing behaviors (Lane, Little, Casey, Lambert, Wehby, Weisenbach & Phillips, 2009; Lane, Kalberg, Lambert, Crnobori & Bruhn, 2010) ROC curve analyses indicate that the SRSS has similar accuracy as the SSBD in predicting students with externalizing behaviors, but less reliability for identifying internalizing behaviors (Lane, Little, Casey, Lambert, Wehby, Weisenbach & Phillips, 2009; Lane, Kalberg, Lambert, Crnobori & Bruhn, 2010).

1.3 Student Risk Screening Scale – Internalizing/Externalizing

In 2012, Lane and colleagues explored if the SRSS could be revised to accurately detect internalizing as well as externalizing behaviors (Lane, Oakes, Harris, Menzies, Cox & Lambert, 2012). During an exploratory study, seven additional indicators of internalizing behaviors were originally added to the SRSS: (a) emotionally flat; (b) shy, withdrawn; (c) sad, depressed; (d) anxious; (e) obsessive-compulsive disorder; (f) lonely; and (g) self-inflicts pain; resulting in the Student Risk Screening Scale-Internalizing and Externalizing 14 (SRSS-IE14) (Lane, Oakes, Harris, Menzies, Cox & Lambert, 2012). A validation study supported the retention of five of the seven additional internalizing items, resulting in the SRSS-IE12 (Lane, Menzies, Oakes, Lambert, Cox & Hankins, 2012). The five internalizing items retained included: (1) emotionally flat; (2) shy, withdrawn; (3) sad, depressed; (4) anxious; and (5) lonely.

There have been a few psychometric studies on the modified version of the SRSS-IE conducted to date (Lane, Menzies, Oakes, Lambert, Cox & Hankins, 2012; Lane, 2015; Lane, Oakes, Cantwell, Schatschneider, Menzies, Crittenden, & Messenger, 2016). Existing studies demonstrate evidence of the adapted tool’s ability to detect students with more covert behaviors. Lane and colleagues (2015) examined the convergent validity of the SRSS-1E12 with the TRF in order to create cut scores that would correspond to student’s specific risk level for internalizing behaviors. At the elementary level, scores range from zero to 15 with three specific risk categories based on these sums: low- (0-1), moderate- (2-3), and high- (4-15) risk (Lane, 2015; Lane, Menzies, Oakes, Lambert, Cox & Hankins, 2012). Follow up studies supported the evidence of retaining the same 5 items proposed by Lane, Oakes et al. (2012) for the internalizing scale. These results provide evidence of the SRSS-IE12's two-factor structure yielding two subscales: the SRSS-E7 (hereafter externalizing scale) and the SRSS-I5 (hereafter internalizing scale).

1.4 Identifying Problem Behaviors in Schools

A variety of other methods exist to identify problem behaviors in schools; determining which data to collect is important for effective data-based decision making (McIntosh, Campbell, Carter & Zumbo, 2009; Newton, Horner, Algozzine, Todd & Algozzine, 2009). Direct observation is typically a more valid and reliable measurement of behavior, given acceptable interobserver agreement, because there is a low level of inference (McIntosh, Campbell, Carter & Zumbo, 2009); however, it is often seen by school personnel as too time-consuming, particularly if the purpose is to identify the level of risk for an entire school (McIntosh, Campbell, Carter & Zumbo, 2009; Briesch & Volpe, 2007). Thus, schools are beginning to rely on indirect measures of behavior to identify levels of problem behaviors in school (McIntosh, Campbell, Carter & Zumbo, 2009). A common form of indirect observation includes standardized behavior rating scales (i.e., SRSS-IE, BASC-2, etc.) (Merrell, 2007). School personnel prefer these methods because of their efficiency and documented reliability and validity (McIntosh, Campbell, Carter & Zumbo, 2009; Merrell, 2007). However, these rating scales also have several weaknesses such as the teacher time needed to complete individual ratings for multiple students (McIntosh, Campbell, Carter & Zumbo, 2009; H. M. Walker & Severson, 1994). Mental health screeners are a proactive, low resource method for the early identification of students who may be at risk for mental health concerns (Ikeda, Neessen, & Witt, 2008). Given the critical nature of prevention and early identification of students at-risk, there is a clear need for feasible and reliable screening tools.

1.5 Office Discipline Referrals

Within schools, a typical response to students who present with externalizing behaviors is to send the student to the school counselor's or administrator's office at which time the student accrues an office discipline referral (ODR) and often another punitive consequence. ODRs are part of a standardized discipline referral process used across the nation to manage and monitor problem behaviors in school settings (Sugai, 2000). According to May et al. (2008), nearly 5,000 schools across the nation document ODRs through the Web-based data entry analysis application School-Wide Information System (SWIS). Students are issued ODRs when a staff member observes them displaying problem behaviors (e.g., defiance, fighting) requiring administrative attention (Sugai, 2000). Previous research has shown that students' ODRs predict a range of negative student outcomes, including school dropout, lower achievement, academic failure, and antisocial behaviors (Predy, 2014; McIntosh, Flannery, Sugai, Braun & Cochrane, 2008). ODR data includes a range of information about the incident, but usually includes information regarding the data, time, location, specific type of behavior, and administrative actions (Sugai, 2000).

When operationally defined (as is required for the use of SWIS), ODRs are reliable and valid indicator for problem behaviors (Irvin, Tobin, Sprague, Sugai & Vincent, 2004). Systematic use includes standard forms and training, as well as systems for recording, reporting, and storing ODR data, all of which, can decrease, but not eliminate the variability in use of ODRs across schools (Predy, 2014; McIntosh, Campbell, Carter & Zumbo, 2009). Rusby and colleagues (2007) found ODRs acquired in kindergarten were more effective than family income in predicting problem behavior in first grade, and first grade ODRs predicted teacher- and parent-reported problem behavior at the end of the year (McIntosh, Campbell, Carter & Zumbo, 2009). Sugai et al. (2000) proposed ODR categories that could be used to categorize students at the end of the school year: zero to one ODRs (Low risk), two to five ODRs (moderate risk), and five or more ODRs (high risk) by end of school year (Predy, 2014; McIntosh, Campbell, Carter & Zumbo, 2009).

Previous studies have used ODRs as both a predictor variable (Mcintosh et al,2009, Pas et al., 2011, Tobin et al., 1996; McIntosh et al., 2010) and outcome variable (McIntosh et al., 2010; Predy et al., 2014; Martinez et al., 2015). As a predictor variable, Tobin et al. (1996) found that the number of ODRs received during the first term in 6th grade significantly predicted referral rates in later terms. More recently, McIntosh et al. (2010) conducted an archival analysis of 990,908 student records from kindergarten to 6th grade and found that receiving one or more ODR by September significantly predicted the number of ODRs received in later months and using a screening criterion of two or more ODRs by October presented the best balance of early and accurate identification.

As an outcome variable, studies today have primarily focused on distinguishing types of ODRs (e.g., aggression, illicit behavior; Girvan, 2017, Predy et al., 2014) or reliability and validity of ODR cut points (i.e. 0-1,2-5, and 6 or more; McIntosh et al., 2009). Irvin and colleagues (2004) presented the preliminary evidence for concurrent validity of ODRs; they found moderate to strong correlations with more established problem behavior measures (i.e. BACS-2). More recently, McIntosh and colleagues (2009), examined the concurrent validity of total ODRs received with the BASC-2 Teacher Report Form, a standardized behavior rating scale for externalizing and internalizing behaviors. The results showed statistically significant correlations between total ODRs received and rating of externalizing behaviors and they also found statistically and clinically significant differences in behavior ratings based on existing

ODR cut points. However, no significant correlation was found between ODRs and ratings of internalizing problems (McIntosh, Campbell, Carter & Zumbo, 2009). Furthermore, many studies have demonstrated good predictive validity of the Student Risk Screening Scale (SRSS; Drummond, 1994) to predict level of behavior risk using ODRs as a behavioral measure (Lane, Parks, Kalberg & Carter, 2007; (Menzies, Lane, 2012). Thus, although research has shown ODRs to be valid for screening students at risk for externalizing behaviors, other validated behavior screeners should still be used to identify those with internalizing behaviors.

1.6 Rationale for Current Study

To date, we are not aware of research examining the predictive validity of the SRSS-IE in relation to ODRs, which would be highly valuable data for schools as they decide whether to invest in the implementation of universal screening for mental health. The purpose of this study was to explore whether universal screening for mental health data collected during the fall of an academic year predicted the number of ODRs that students accrue throughout the academic year. We are not aware of another study examining if SRSS- IE internalizing and externalizing scales predict ODRs in elementary children.

1.7 Research Question

Through this study, we aim to answer the following research question:

1. Does the SSRS-IE predict end of year ODRs?

CHAPTER 2

METHODS & PROCEDURES

2.1 Context

This is a federally funded study with the Department of Education. The purpose of the project is to increase wellness and resilience in youth by setting up universal screening for mental health in three districts. Members of the research team provided training and technical assistance to school districts related to universal screening for mental health. Also, trained researchers analyzed all screening data, created reports with the results of the screening data, and provided those reports to the schools that participated in screening.

2.2 Participants and Settings

Participants for this study are students in three elementary schools in County M. According to the 2015 United States Census Bureau, the population of County M is 44.2% Black, 42.4% White, and 7.27% Hispanic. County M has a median annual income of $42,206, which is less than the median annual income of $56,516 in the United States.

Participants were 1,201 kindergarten through fifth grade students, who were rated by their homeroom teachers (N=68) on the SRSS-IE during fall of the 2016-2017 school year (see Table 1). The student sample was disproportionately Black: 86% (School D), 70% (School C), and 68% (School W), ranging from 24% to 42% higher than the county average for this population.

2.3 Procedures

After securing university and district-level human subjects research approval, de-identified student-level data were collected from each school during the 2016-2017 academic year. Each school administered the SRSS-IE screener according to the procedures determined by the schools' leadership team. During a scheduled faculty meeting prior to the 2016-2017 school year, teachers were introduced to the purpose of the SRSS-IE and taught how to complete the screener. All schools administered the screen in the Fall (4-6 weeks into the school year) and again in the Spring (6 weeks prior to end of school year).

All de-identified data collected from the sites were entered into an Excel database, which contained formulas to compute scores. The accuracy of the scores were checked three times by the research team members to ensure the computation of scores was correct.

2.4 Measures

OFFICE DISCIPLINE REFERRAL: As mentioned previously, ODRs are standardized forms used to document problem behaviors in school settings (Sugai, 2000). The district in the present study uses ODRs to document serious problem behaviors and has identified a common ODR form which list problem behaviors that warrant an ODR. The total number of ODRs issued during the school year was used as the outcome variable for analyses. For this study, the ODR total included all ODRs issued from August through May, regardless of type (i.e. fighting, disrespect, etc.).

SRSS-IE: Fall externalizing and internalizing total scores (continuous variables) were used as the main predictor variables for analyses. As previously stated, the SRSS-IE is an adapted version of the SRSS (Drummond, 1994). The instrument contains a list of all students on a teacher's roster in the first column, with twelve items listed across the top row (Figure 1). Items include the original seven items constituting the externalizing scale - (a) steals; (b) lies, cheats, sneaks; (c) behavior problems; (d) peer rejection; (e) low achievement; (f) negative attitude; and (g) aggressive behaviors; and a five-item internalizing scale - (h) emotionally flat; (I) shy, withdrawn; (j) sad, depressed; (k) anxious; and (l) lonely. Teachers complete this measure by rating each student on their roster on each item using a 4-point Likert scale: never = 0, occasionally = 1, sometimes = 2, and frequently = 3. A total score for each scale is computed by summing item scores for each student, with total scores ranging from zero to 21 for the externalizing scale and zero to 15 for the internalizing scale. Higher scores indicated higher levels of behavior risk.

Office Disciplinary Referrals (October): In this study, the Office Discipline Referrals October (ODROCT) variable includes ODRs earned during the months of August, September, and October. As mentioned earlier, previous studies have shown preliminary ODRS to be a valid measure for predicting future ODRs (Predy, 2014; MnIntosh, 2010), thus by including these variables in the model we have a validated standard to measure our screeners against.

Demographic Variables

Grade. This measure represents the grade of the student during the time of screening. The ODR literature consistently shows the number of ODRs increase as children move from elementary to middle school and a more significant increase is seen between middle to high school (National Center for Education Statistics [NCES], 2010). Thus, grade will be included as a categorical predictor (i.e., K, 1, 2, 3, 4 & 5) to assess if it adds to the prediction of year-end ODRs.

Race/ Ethnicity. Emerging evidence in the ODR literature has shown that African American and Latino students disproportionally receive more ODRs compared to their White peers (Girvan, 2017; Kaufman et al., 2010; Skiba et al., 2008),). Race and ethnicity were included in the model as a categorical variable with 4 groups: Black, White, all Hispanics, and other races (i.e., Asian, Multiracial, & American Indian)

Gender. As with other measures of student behavior (Koth, Bradshaw & Leaf, 2009), male students are at greater risk for receiving an ODR (Bradshaw, Mitchell, O'Brennan et al., 2010; Kaufman et al., 2010). Each student's gender was included in the model as a dichotomous variable (i.e., 1=male, 0=female).

All non-screener variables included are relevant sources of variance that may account for change in ODR. By including these variables in the model, we are accounting for their variance in relation to our screener scales.

2.5 STATISTICAL ANALYSIS

ODR data is count data with a positive distribution (i.e. more students receive 0 ODRs), so we used non-parametric methods for analysis (Gardner, Mulvey & Shaw, 1995). Outcomes that are count data, ordinal, and subject to outliers or measured imprecisely are difficult to analyze with parametric methods as their statistical assumptions are often violated. In cases when violations occur, nonparametric tests may be the only way to analyze these data (Ophthalmol., 2009). Nonparametric tests are based on fewer assumptions than traditional parametric tests (i.e., they do not assume the outcome to be normally distributed) (Ophthalmol., 2009). For descriptive statistics and consideration of model inclusion non-parametric approaches were used such as, Spearman correlation, Mann-Whitney U test, and Kruskal–Wallis H test. For model building poisson regressions, a commonly used method for analyzing count data, will be utilized (Bolker et al., 2009).

Before regression analyses were conducted, various bivariate analyses were conducted to determine which variables to include in the model as the best predictors of ODRs. Pearson's correlation is traditionally used to analyze the relationship between two variables, however, this method assumes the data are normally distributed and randomly sampled (UWE, 2018). Because we are comparing ranked data, (i.e., behavior problem risk measured by SRSS-IE and ODR data), spearman's rho was used to analyze the association between our continuous variables: ODR Total, October ODRs and the SRSS internalizing and externalizing scales. Group comparisons for our sociodemographic variables were conducted using Kruskal-Wallis and Mann-Whitney U test. The t-test and ANOVA are commonly used statistical test for comparing respective means of two or more independent groups, but these parametric tests require that the data is normally distributed and the variances between the groups are equal (Ophthalmol., 2009). The Mann-Whitney and Kruskal-Wallis test are commonly used nonparametric tests used for data that is not normally distributed (Ophthalmol., 2009). The Mann-Whitney test is the alternative to the t-test and analyzes the data in terms of rank rather than raw scores, which allows analyses to be run on non-normally distributed data. The Kruskal-Wallis test (KW) extends the MW test and is used when there are more than two groups, similar to the ANOVA. Race and grade differences were analyzed using Kruskal-Wallis H test and gender differences were analyzed using Mann-Whitney U test. Variables displaying p values <=.2 were selected to be included in the final model.

In addition to variable selection, we also looked at relations between the SRSS's internalizing and externalizing scales and other variables. Spearman rho correlations were used to examine the relationship between the internalizing and externalizing scales and October ODRs. Again, Kruskal-Wallis tests were used to analyze race and grade differences and the Mann-Whitney U test was used to examine gender differences.

To determine if the SRSS internalizing and externalizing scales served as predictors of total number of ODRs, a series of models were first fit to determine if covariates such as, October ODRs, race, grade, and gender add to the prediction of our outcome. For the first two models, M1 and M2, we regressed the ODR total on only externalizing scale or internalizing scale total. We next regressed ODR total on the externalizing and internalizing scales together(M3). For Model 4, we added our preliminary ODR variable to the model**.** Model 5 included all variables included in model 4 plus all relevant sociodemographic variables. Poisson regressions models were considered for model building as this is a widely used method when count variables are used as the dependent variable in analysis.

The Akaike information criterion (AIC) is a measurement of goodness of fit when using count variables. For model comparison, the model with the smallest Akaike Information Criterion (Akaike, 1973) will be considered the best-fitting model. All analyses were done using SAS 9.4.

Reliability

Internal consistency. To assess internal consistency of the SRSS-IE, we computed alpha coefficients for the fall administrations of the SRSS-IE. Cronbach's alphas exceeding .70 indicated high internal consistency (Nunnally & Bernstein, 1994).

CHAPTER 3

RESULTS

Descriptive Analyses

Initially, bivariate analyses were conducted to select the best subset of sociodemographic predictors for our model and groups that did not have significantly different ODR totals ($p < 0.2$) were excluded from the final model. In our study sample, the total number of ODRs ranged from 0 to 20, with a mean of 0.48. Spearman rho results showed strong statistically significant correlations between ODR total and both the externalizing (*rho* = .35, $p < .01$) and internalizing (*rho* = 0.08, $p < .05$) scales. Significant associations were also found between ODR totals and October ODRs (*rho* = 0.6478, $p < .05$). Group comparisons showed a statistically significant mean difference in total ODR scores between the 4 racial groups ($H = 9.58$, $p < .01$). As expected, Black students had a higher number of ODRs accumulated over the entire school year than Hispanic students ($U = 33725.50$, $p < .05$). Mann-Whitney U test indicated males had more year-end ODRs than females (U = 424274 .00, $p < .0001$). No differences were found by grade ($p > 0.2$). Based on these results, all demographics except for grade were included in the final model. Grade was not included because there were no significant differences found between the groups ($p > 0.2$).

Descriptive Analyses of Universal Screening Data

To assess the difference in SRSS-IE scores by race, gender, and grade, bivariate analyses were also conducted for both the externalizing and internalizing subscales. Moderate significant correlations were found between the externalizing scale and both the internalizing scale (*rho* = 0.3294, $p < .05$) and ODR October data (*rho* = 0.258, $p < .05$). Kruskal–Wallis H (KW) test indicated significant mean differences in externalizing scale total scores by race ($H = 23.66$, p <

.0001). Follow up MWU indicated Black students were significantly higher than Hispanic Groups (U = 1.21, p < .05). There was not a significant difference found between Black students and the other racial/ethnic groups. No significant differences were found for externalizing scores by grade. Results from Mann-Whitney test indicated a significant difference in externalizing scores between males and females (U = 318593.00, p < .0001.); males tended to score higher on the externalizing scale than their female counterparts.

For the internalizing scale, KW test indicated significant mean differences by grade (H = 15.2299, p < .0001). Follow up MWU tests showed third grades had significantly higher internalizing scores than first (U = 26878, p < .05) and fourth graders (U = 44411, p < .01). MWU test also revealed a significant difference between males and females (U = 342626.00, p = .05), again males scored higher. No significant differences were found by race for the internalizing scale. Test statistics and p values for all bivariate comparison are presented in Tables 2 and 3.

Predictors of Office Discipline Referrals

We initially fit a series of five Poisson models separately to predict total ODRs: Model 1 looked at the relationship between externalizing scores to ODRs; Model 2 included only internalizing scores; Model 3 included both the externalizing and internalizing scales; in Model 4 the ODR preliminary variable was added to the model to examine its influence; Model 5 included the three previously mentioned variables plus race and gender. Based on AIC statistics, our decision is that the five-variable model, including the internalizing and externalizing scales, October ODRs, race and gender, had better fit than the other models, so this was the model selected as our final model.

In the final Poisson model SRSS-IE externalizing scales and October ODRs positively predicted and internalizing scales negatively predicted year-end ODRs (all *ps* $< .01$). Compared to kindergartners, first, third, fourth, and fifth graders had greater year-end ODRs (all *ps* $< .01$ except 2nd grade), and race groups did not differ ($p > .05$).

CHAPTER 4

DISCUSSION

Several studies have examined the SRSS's ability to predict important behavior outcomes using ODR data (Menzies, Lane, 2012; Lane, Parks, Kalberg & Carter, 2007; Lane, 2010), but no study to date has examined the predictive validity of the revised tool, SRSS-IE, and its relationship to school behavior data. This study helps fill this gap by providing initial evidence of the SRSS-IE's ability to predict year-end ODRs. Results from our study support previous studies finding that externalizing scale total scores predict the number of ODRs received at the end of the school year, with higher levels or risk being associated with a higher number of ODRs at year-end. Our study is unique in its provision of evidence for a significant negative relationship between internalizing scores and year-end total ODRs (i.e., higher rates of internalizing behaviors were associated with fewer ODRs at year-end). Our study is also unique its use of Poisson regression analysis, which is more robust than may previous analytic methods used for research on the SRSS and SRSS-IE (e.g., MANOVA). Finally, previous research on both the SRSS and SRSS-IE screeners have mainly used predominately White samples (Lane, Parks, Kalberg & Carter, 2007; Lane, 2010; Lane, 2015). This study adds to the current literature, by providing evidence of the SRSS-IE's utility in a predominately Black sample.

Results from the current study resonates with previous validation studies for the SRSS at the elementary level. Similarly, many past studies examined the predictive validity of the externalizing scale using ODR data (Lane, Parks, Kalberg & Carter, 2007; Menzies, Lane, 2012; Lane, 2010); these studies also found externalizing scores predicted year-end ODR totals. Although our results were similar, it is important to note that the previous studies generally used parametric approaches, (Lane, Parks, Kalberg & Carter, 2007; Lane, 2010) and another study used logistic regression models (Menzies, Lane, 2012). Our study differed in the fact that we used Poisson regressions for analysis which is a more robust nonparametric regression technique that is used with count data like ODRs that have heavy tailed distributions.

As mentioned previously, we are not aware of any other studies examining the predictive validity of the SRSS-IE, which was modified to include a scale for screening children at risk of internalizing behaviors. Mcintosh et al. in 2009, however, examined the concurrent validity of number of ODRs received with a contemporary standardized behavior rating scale (BASC-2) and found strong correlations between ODRs and ratings of externalizing behaviors, but no significant relationship was found between internalizing behaviors and ODRs. In our literature search we identified no other studies where internalizing scores predicted ODRs. Thus, our study is unique in the fact the fact that a significant relationship was found between the internalizing scale and ODR totals. No previous studies have found this relationship.

Support of the SRSS-IE's utility for predicting problem behaviors in school is highlighted by the significant predictive utility even when October ODRs were included in our models. ODRs received by October are a valid measurement to identify future problem behaviors in elementary students (McIntosh et al., 2010), and therefore a stringent covariate to use in our models. The fact that the SRSS-IE externalizing and internalizing scales predict ODRs even when controlling for October ODRs provides strong evidence for the predictive validity of these scales and shows the potential utility for these scales for schools as they provide more information about year-end ODRs than October ODRs alone.

Our results are consistent with previous studies looking at socio-demographic variables in ODRs. We found Black students had significantly higher total ODRs at year-end than Hispanics and Other ethnic/racial groups. These results are similar to the literature, as previous studies show Black students disproportionally receive more ODRs than their White peers (Girvan, 2017). Our study is unique in the fact that no significant differences in total ODRs were found between Black and White students, however there were significant differences found between Black and Hispanics and Black and other ethnic groups. These findings may be unique to our sample; future research should seek to replicate.

In terms of psychometric properties, the alpha reliability coefficients were like those found in previous studies (Lane, Oakes, Harris, et al., 2012; Lane, Menzies, Oakes, et al., 2012). For example, the externalizing value in our study was .83, just slightly higher than .82 reported by both Lane, Oakes, Harris, et al. (2012) and Lane, Menzies, Oakes, et al. (2012). Similarly, SRSS-IE internalizing values were .75 in our study and .72 (Lane, Oakes, Harris, et al., 2012) and .77 (Study 1, Lane, Menzies, Oakes, et al., 2012) in the previous studies. These consistent result show that these scales have good reliability across multiple different samples.

In summary, early identification and intervention for students at risk for behavior difficulties lead to more positive long-term outcomes. Research has taught us that the likelihood of a child receiving services remains low throughout elementary and increases substantially once children transition to middle school, thus there is a significant need for early intervention/universal screening to reduce the number of children needing services later in life. These findings add to the current literature by providing compelling, yet preliminary, evidence that the SRSS-IE, is predictive of problem behaviors as measured by ODRs. Again, these results support previous studies demonstrating the externalizing scales ability to predict year-end behavior risks as measured by ODRs. Our study also offers preliminary evidence that the internalizing scale is significantly related to ODRs. This data provides support for the use of screener data in schools to predict and prevent problem behaviors opposed to relying solely on the use of more reactive data such as ODRs.

LIMITATIONS

There are several key considerations that warrant attention when interpreting findings from this study. First, our sample provides initial evidence of the SRSS-IE's utility in a predominately Black sample, but future studies still need to be conducted with a greater diversity of participants to establish generalizability of results. Our sample also had a high portion of students receiving 0 ODRs throughout the school year (n = 82%), which is expected when using count data. The poisson regression is a standard method to use for analyzing count data, however it cannot account for overdispersion caused by excessive zeros (Loyes et al., 2011). Future studies may want to consider more rigorous statistical methods such as Zero-inflated poisson models which has the ability to account for overdispersion caused by excessive zeros. Additionally, this study is subject to many of the same limitations of other analyses of extant data. We must be careful when comparing ODRs across schools, as external validity may be limited due to inconsistencies within schools in completing referral forms. In Model 4, ODRs were used as both predictors and outcomes variables thus the results should be interpreted with some caution because this is single source analysis which may result in inflated test statistics (Predy, 2014, Mcintosh et. al. 2010).

FUTURE RESEARCH AND IMPLICATIONS

Relying on ODR data alone for data-based decision making in school, may be ineffective as it may not capture students with internalizing behaviors. Therefore, universal screening should be done in coordination with collecting this data to ensure that students with internalizing behaviors are detected with the same accuracy as students with externalizing behaviors. It is imperative that future studies assess the predective validity of the SRSS-IE with other behavior outcome variables related to internalizing behaviors. Additionally, future studies need to assess the long-term predictive validity of the SRSS-IE (e.g., 2, 5, and even 10 years following the initial nomination) to provide evidence of the tools long term predictability.

TABLES AND FIGURES

Table 1: County M Descriptive Statistics

School	**School D** **n = 474** % (n)	**School C** **n = 325** % (n)	**School W** **n = 402** % (n)	Total N = 1201 % (n)
Variable				
Gender				
Males	50.84 (241)	52.92 (172)	50.00 (201)	51.12 (614)
Females	49.16 (233)	47.08 (153)	50.00 (201)	48.88 (587)
Grade				
K	16.67 (79)	21.23 (69)	16.42 (66)	17.82 (214)
1	12.03 (57)	17.23 (56)	9.95 (40)	12.74 (153)
2	18.78 (89)	13.54 (44)	18.41 (74)	17.24 (207)
3	17.93 (85)	16.62 (54)	20.65 (83)	18.48 (222)
4	18.99 (90)	17.85 (58)	16.92 (68)	17.99 (216)
5	15.61 (74)	13.54 (44)	17.66 (71)	15.74 (189)
Race/Ethnicity				
Black[≠]	86.50 (410)	70.15 (228)	71.14 (286)	76.94 (924)
White[≠]	2.74 (13)	4.31 (14)	18.91 (76)	8.58 (103)
All Hispanics	2.74 (13)	18.46 (60)	3.23 (13)	7.16 (86)
Other	8.02 (38)	7.08 (23)	6.72 (27)	7.33 (88)

[≠]Non-Hispanic

Table 2: Bivariate analyses for SRSS-IE Scale Scores and ODR Totals

	SRSS – E7	**SRSS-I5**	**ODRTOL**
Gender			
W(df)	318593.00 (1) ***	342626.00 (1) *	424274 .00 (1) ***
Male (n=614)			
Median	2	0	0
Mean	3.45	0.79	0.74
SD	4.05	1.76	2.21
Female (n=587)			
Median	1	0	0
Mean	2.07	0.54	0.20
SD	2.81	1.39	0.97
Race/Ethnicity			
H (df)	23.66 (3) ^^^	1.9 (3)	10.04 (3) ^
Black (n=924)			
Median	2	0	0
Mean	$3.04_{A, B}$	0.68	0.52_{C}
SD	3.73	1.59	1.77
White (n = 103)			
Median	1	0	0
Mean	2.39	0.86	0.42
SD	3.18	1.91	2.28
Hispanic (n=86)			
Median	1	0	0
Mean	1.41_{A}	0.47	$0.17_{C, D}$
SD	2.13	1.24	0.74
Other (n=88)			
Median	1	0	0
Mean	1.82_{B}	0.54	0.38_{D}
SD	2.78	1.46	0.99
Grade			
H (df)	5.3557 (5)	15.2299 (5) ^^	10.6519 (5)
K-5 (n= 214)			
Median	1	0	0
Mean	2.448	0.7354	0.2663
SD	3.358	1.4853	1.202
1 (n=153)			
Median	2	0	0
Mean	3.124	0.496_{C}	0.4640_{F}
SD	3.950	1.262	1.630
2 (n=207)			
Median	2	0	0
Mean	2.782	0.550	$0.5265_{G, H}$
SD	3.443	1.443	2.0804
3 (n = 222)			
Median	2	0	0
Mean	2.936	0.9819	$0.4954_{F, G, J}$
SD	3.446	$2.1313_{C, E}$	1.9162
4 (n=216)			
Median	1	0	0
Mean	2.680	0.5833_{E}	$0.4537_{J, K}$
SD	3.666	1.5165	1.332
5 (n = 189)			
Median	2	0	0
Mean	2.830	0.735	$0.7037_{H, K}$
SD	3.652	1.485	2.115

Notes: *** = W-test, p< .0001; ** = W-test, p < .01; * = W-test, P < .05; ^^^ = H-test, p< .0001; ^^ = H-test, p < .01; ^ = H-test, P < .05. W- test =. H-test =. For group comparisons all subgroups sharing alphabetical subscripts are significantly different at p<.05 on MWU test.

Table 3: Intercorrelations among ODRs and SRSS-IE Scales

	ODRTOL	SRSS-E7	SRSS-I5	ODRPRE
ODRTOL	--	**.35289****	**.07743****	**0.6478****
SRSS-E7		--	**.3294****	**0.2584****
SRSS-I5			**--**	**0.01570**
ODRPRE				**--**

Note. ODRTOL=Total number of ODRs earned during the school year. ODRPRE= ODRs earned during the months of August, September and October. SRSS-E7 = Externalizing Scale; SRSS-I5= Internalizing Scale. Spearman correlation used for analyses.
***p<.05. **p<.01.**

Table 4: Results of Poisson Model Selection

Variable	M1	M2	M3	M4	M5
Ext.	0.186*** [0.172, 0.201]			0.141*** [0.121, 0.162]	0.127*** [0.106, 0.149]
Int.		0.022 [-0.026, 0.070]	0.221*** [0.205, 0.237]	-0.072* [-0.129, -0.016]	-0.08568** [-0.1436, -0.0276]
ODROct.			-0.224*** [-0.282, -0.1667]	0.581*** [0.528, 0.634]	0.5446*** [0.4901, 0.5991]
Gender[1]					-0.3489*** [-0.4571, -0.2408]
Race					
Black					Reference
White					0.1718 [-0.1423, 0.4859]
Hispanic					-0.5995* [-1.1374, -1.1374]
Other					0.0055 [-0.3451, 0.3560]
Model AIC	2627.9837	3146.6527	2552.9651	2173.9837	2132.1545

Note: ODROct= ODRs earned during the months of August, September and October. Ext. = Externalizing Scale (SRSS-E7); Int.= Internalizing Scale (SRSS-I5). *p < .05. **p < .01. ***p < .0001.
[1]Male is reference group.

Table 5: Cronbach's Coefficient Alphas

		Standardized Variables	
		R with total (<.35)	Alpha[1]
Time	**Item**	**Externalizing Items (7)**	
Fall			0.83
(n = 1,201)	1. Steal	0.47	0.82
	2. Lie, cheat, sneak	0.65	0.79
	3. Behavior Problem	0.71	0.78
	4. Peer Rejection	0.51	0.81
	5. Low Academic Achievement	0.37	0.83
	6. Negative Attitude	0.65	0.79
	7. Aggressive Behavior	0.65	0.79
		Internalizing Items (5)	
Fall			0.75
	1. Emotionally Flat	0.53	0.71
	2. Shy, withdrawn	0.55	0.71
	3. Sad, depressed	0.64	0.67
	4. Anxious	**0.31**	0.79
	5. Lonely	0.62	0.68

[1]In the column labeled *Alpha*, the first alpha value is the overall alpha level. Subsequent values refer to the alpha values if the item had been deleted from the scale.

Figure 1: Example of the Student Risk Screening Scale-Internalizing and Externalizing 12 (SRSS-IE12)

Student Risk Screening Scale - Internalizing and Externalizing (SRSS-IE)
MIDDLE and HIGH SCHOOL USE 2016 - 2017

DATE:

TEACHER NAME:

PERIOD RATED:

Note: Peer rejection is summed in the SRSS-E and SRSS-I TOTAL scores.

Shaded items are summed to compute the SRSS-I TOTAL score; SRSS-IE TOTAL scores are under construction and should not be use for decision making. The item Peer Rejection is only added once to the SRSS-IE TOTAL score.

0 = Never
1 = Occasionally
2 = Sometimes
3 = Frequently
Use the above scale to rate each item for each student.

Student Last Name	First Name	Teacher	Grade	Gender	Race	Student ID	Count	Steal	Lie, Cheat, Sneak	Behavior Problem	Peer Rejection	Low Academic Achievement	Negative Attitude	Aggressive Behavior	Emotionally Flat	Shy; Withdrawn	Sad; Depressed	Anxious	Lonely
Example: Smith	*Sally*	*Jones*	*1ST*	*F*	*H*	*11111*	0	*0*	*0*	*3*	*1*	*3*	*3*	*3*	*2*	*2*	*2*	*3*	*0*
Example: Lane	*Scarlett*	*Smith*	*2ND*	*F*	*M*	*112341*	0	*0*	*0*	*3*	*1*	*3*	*3*	*3*	*0*	*0*	*1*	*2*	*0*
							1												
							2												
							3												
							4												
							5												
							6												
							7												
							8												

REFERENCES

Akaike, H. (1973). Information theory and an extension of the maximum likelihood principle. In B.N. Petrox and F. Caski (Eds.), Second international symposium on information theory (pp. 267–281). Budapest: Akademiai Kiado.

Albers, C. A., Glover, T. A., & Kratochwill, T. R. (2007). Introduction to the special issue: How can universal screening enhance educational and mental health outcomes? *Journal of School Psychology, 45*(2), 113-116. doi:10.1016/j.jsp.2006.12.002

Am J Ophthalmol. 2009 Apr; 147(4): 571–572. doi:10.1016/j.ajo.2008.06.031

Ballinger, Kristen M., "Impact of Universal Social-Emotional and Behavioral Screening Among Middle School Students: A Multistage Approach to Identification" (2016). *UNLV Theses, Dissertations, Professional Papers, and Capstones*. 2633. http://digitalscholarship.unlv.edu/thesesdissertations/2633

Bolker BM, Brooks ME, Clark CJ, Geange SW, Poulsen JR, Stevens MHH, White JSS. 2009. Generalized linear mixed models: a practical guide for ecology and evolution. *Trends in Ecology & Evolution* 24:127-135

Bradshaw, C. P., Buckley, J., & Ialongo, N. (2008). School-based service utilization among urban children with early-onset educational and mental health problems: The squeaky wheel phenomenon. School Psychology Quarterly, 23, 169–186. doi.org/10.1037/10453830.23.2.169 – (Bradshaw, Buckley, Ialongo, 2008) Briesch, A. M., & Volpe, R. J. (2007). Important considerations in the selection of progress monitoring measures for classroom behaviors. *School Psychology Forum*, 1, 59-74.

Burnham, K.P., & Anderson, D.R. (2002). Model selection and multi-model inference: A practical information-theoretic approach (2nd ed.). New York: Springer-Verlag.

Chafouleas, S. M., Kilgus, S. P., & Wallach, N. (2010). Ethical dilemmas in school-based behavioral screening. *Assessment for Effective Intervention, 35*(4), 245-252.

Chafouleas, S. M., Volpe, R. J., Gresham, F. M., & Cook, C. R. (2010). School-based behavioral assessment within problem-solving models: Current status and future directions. *School Psychology Review, 39*(3), 343-349.

Crawley MJ. 2007. *The R book*. United Kingdom: John Wiley & Sons Ltd.

Drummond, T. (1994). The Student Risk Screening Scale (SRSS). Grants Pass, OR: Josephine County Mental Health Program.

Flannery, K. B., Fenning, MnIntosh et al. (2014). "Effects of School-Wide Positive Behavioral Interventions and Supports and Fidelity of Implementation on Problem Behavior in High Schools." School Psychology Quarterly 29(2): 111-124.

Gardner, W., Mulvey, E. P., & Shaw, E. C. (1995). Regression analyses of counts and rates: Poisson, overdispersed Poisson, and negative binomial models. *Psychological Bulletin, 118*(3), 392-404. http://dx.doi.org/10.1037/0033-2909.118.3.392

Girvan, E. J., et al. (2017). "The Relative Contribution of Subjective Office Referrals to Racial Disproportionality in School Discipline." School Psychology Quarterly 32(3): 392-404.

Glover, T. A., & Albers, C. A. (2007). Considerations for evaluating universal screening assessments. *Journal of School Psychology, 45*(2), 117-135. doi:10.1016/j.jsp.2006.05.005

Goodman, R. (1997). The Strengths and Difficulties Questionnaire: A research note. Journal of Child Psychology and Psychiatry, 38, 581–586. doi.org/10.1111/j.1469-7610.1997.tb01545.x

Gresham, F. M., & Elliott, S. N. (2008) Social Skills Improvement System: Rating scales. Bloomington, MN: Pearson Assessments.

Harrison X. A., Using observation-level random effects to model overdispersion in count data in ecology and evolution. PeerJ 2, e616 (2014).

Hilbe JM. 2011. *Negative binomial regression* (2nd edition). Cambridge: Cambridge University Press.

Ikeda, M. J., Neessen, E., & Witt, J. C. (2008). Best practices in universal screening. In A. Thomas & J. Grimes (Eds.), Best practices in school psychology (5th ed., Vol. 2, pp. 103-114). Bethesda, MD: National Association of School Psychologists.

Irvin, L. K., Tobin, T. J., Sprague, J. R., Sugai, G., & Vincent, C. G. (2004). Validity of office discipline referral measures as indices of school-wide behavioral status and effects of school-wide behavioral interventions. *Journal of Positive Behavior Interventions, 6,* 131–147. http://dx.doi.org/10.1177/10983007040060030201 - (Irvin, Tobin, Sprague, Sugai & Vincent, 2004)

Kamphaus, R. W., & Reynolds, C. R. (2007). BASC-2 Behavioral and Emotional Screening System manual. Bloomington: Pearson.

Kauffman, J. M. (2001). Characteristics of emotional and behavioral disorders of children and youth (7th ed.). Upper Saddle River, NJ: Merrill/Prentice Hall.

Kim, E. K., Furlong, M. J., Dowdy, E., & Felix, E. D. (2014). Exploring the relative contributions of the strength and distress components of dual-factor complete mental health screening. *Canadian Journal of School Psychology, 29*(2), 127–140. doi: 10.1177/0829573514529567 – (Kim, Furlong Dowdy & Felix, 2014)

Lane, K. L., Kalberg, J. R., Lambert, E. W., Crnobori, M., & Bruhn, A. L. (2010). A Comparison of Systematic Screening Tools for Emotional and Behavioral Disorders A Replication. Journal of Emotional and Behavioral Disorders, 18(2), 100-112. doi:10.1177/1063426609341069 – (Lane, Kalberg, Lambert, Crnobori & Bruhn, 2010)

Lane, K. L., Little, M. A., Casey, A. M., Lambert, W., Wehby, J., Weisenbach, J. L., & Phillips, A. (2009). A Comparison of Systematic Screening Tools for Emotional and Behavioral Disorders. Journal of Emotional and Behavioral Disorders, 17(2), 93-105. doi:10.1177/1063426608326203 – (Lane, Little, Casey, Lambert, Wehby, Weisenbach & Phillips, 2009)

Lane, K. L., Menzies, H. M., Oakes, W. P., Lambert, W., Cox, M., & Hankins, K. (2012). A Validation of the Student Risk Screening Scale for Internalizing and Externalizing Behaviors: Patterns in Rural and Urban Elementary Schools. Behavioral Disorders, 37(4), 244-270. – (Lane, Menzies, Oakes, Lambert, Cox & Hankins, 2012)

Lane, L. K., Oakes, W. P., Cantwell, E. D., Schatschneider, C., Menzies, H., Crittenden, M., & Messenger, M. (2016). Student Risk Screening Scale for Internalizing and Externalizing Behaviors: Preliminary Cut Scores to Support Data-Informed Decision Making in Middle and High Schools. *Behavioral Disorders, 42*(1), 271-284. doi:10.17988/bd-16-115.1 – (Lane, Oakes, Cantwell, Schatschneider, Menzies, Crittenden, & Messenger, 2016)

Lane, K. L., Oakes, W. P., Harris, P. J., Menzies, H. M., Cox, M., & Lambert, W. (2012). Initial Evidence for the Reliability and Validity of the Student Risk Screening Scale for Internalizing and Externalizing Behaviors at the Elementary Level. Behavioral Disorders, 37(2), 99-122. – (Lane, Oakes, Harris, Menzies, Cox & Lambert, 2012)

Lane, K. L., Parks, R. J., Kalberg, J. R., & Carter, E. W. (2007). Systematic screening at the middle school level: Score reliability and validity of the student risk screening scale. Journal of Emotional and Behavioral Disorders, 15(4), 209-222 – (Lane, Parks, Kalberg & Carter, 2007)

Lane, K. L., et al. (2010). "Score Reliability and Validity of the Student Risk Screening Scale: A Psychometrically Sound, Feasible Tool for Use in Urban Middle Schools." Journal of Emotional and Behavioral Disorders 18(4): 211-224.- (Lane, 2010)

Lane, K. L., et al. (2015). "Student Risk Screening Scale for Internalizing and Externalizing Behaviors: Preliminary Cut Scores to Support Data-Informed Decision Making." Behavioral Disorders 40(3): 159-170. – (Lane, 2015)

Loeys, T., Moerkerke, B., Smet, O. D., & Buysse, A. (2011). The analysis of zero-inflated count data: Beyond zero-inflated Poisson regression. *British Journal of Mathematical and Statistical Psychology, 65*(1), 163-180. doi:10.1111/j.2044-8317.2011.02031.x

May, S., Ard, W. I., Todd, A. W., Horner, R. H., Glasgow, A., *&* Sugai, G., e! al. (2008). *School-Wide Information System homepage, \riterr\etsite:* http:/www.swis.org (Accessed)uly *2,* 2008).

McIntosh, K., Campbell, A. L., Carter, D. R., & Zumbo, B. D. (2009). Concurrent validity of office discipline referrals and cut points used in schoolwide positive behavior support. Behavioral Disorders, 34, 100–113. – (McIntosh, Campbell, Carter & Zumbo, 2009)

McIntosh. K,, Flannery, K. B., Sugai, G., Braun, D., & Cochrane, K. L. (2008). Relationships between academics and problem behavior in the transition from middle school to high school. *Journal of Positive Behavior Interventions, 10,* 243-255. – (McIntosh, Flannery, Sugai, Braun & Cochrane, 2008)

McIntosh, K,, Frank, J. L. & Spaulding, S. A. (2010). Establishing research-based trajectories of office discipline referrals for individual students. *School Psychology Review, 39*, 380-394. – (McIntosh, Frank & Spaulding, 2010)

Menzies, H. M., & Lane, K. L. (2012). Validity of the Student Risk Screening Scale. Journal of Emotional and Behavioral Disorders, 20(2), 82-91. doi:10.1177/1063426610389613 – (Menzies, Lane, 2012)

Merikangas, K., Avenevoli, S., Costello, J., Kortez, D., & Kessler, R. (2009). National comorbidity survey replication adolescent supplement (NCS-A): Background and measures. *Journal of the American Academy of Child and Adolescent Psychiatry, 48*(4),367-379.

Merikangas, K. R., et al. (2010). "Lifetime Prevalence of Mental Disorders in U.S. Adolescents: Results from the National Comorbidity Survey Replication-Adolescent Supplement (NCS-A)." Journal of the American Academy of Child and Adolescent Psychiatry 49(10): 980-989. – (Merikangas, 2010)

Merrell, K. W. (2007). *Behavioral, social, and emotional assessment of children and adolescents* (3rd ed.). Mahwah, NJ: Erlbaum. – (Merrell, 2007

Muthen, L., & Muthen, B. (2005). Mplus® statistical analysis with latent variables: User's guide. Los Angeles, CA: Muthen & Muthen.

National Center for Education Statistics. (2010). *Indicators of school crime and safety: 2010.* Washington, DC: Bureau of Justice and Statistics. Retrieved from http://nces.ed.gov/programs/crimeindicators/crime indicators2010/figures.asp

Newton, J. S., Horner, R. H., Algozzine, R. F., Todd, A. W., & Algozzine, K. M. (2009). Using a problem-solving model to enhance data-based decision making in schools. In W. Sailor, G. Dunlap, G. Sugai, & R. H. Horner (Eds.), *Handbook of positive behavior support* (pp. 551-580). New York: Springer. – (Newton, Horner, Algozzine, Todd, & Algozzine, 2009)

Oakes, W. P., Lane, K. L., Cox, M. L., & Messenger, M. (2014). Logistics of behavior screenings: How and why do we conduct behavior screenings at our school? *Preventing School Failure, 58*(3), 159–170. doi: 10.1080/1045988X.2014.895572 – (Oakes, Lane, Cox &Messenger, 2014)

Predy, L., McIntosh, K., Frank, J. L., & Flitchcock, J. (2014). Utility of Number and Type of Office Discipline Referrals in Predicting Chronic Problem Behavior in Middle Schools. School Psychology Review, 43(4), 472-489. – (Predy, McIntosh, Frank, & Flitchcock, 2014)

Renshaw, T. L., Eklund, K., Dowdy, E., Jimerson, S. R., Hart, S. R., Earhart, J., & Jones, C. N. (2009). Examining the relationship between scores on the behavioral and emotional screening system and student academic, behavioral, and engagement outcomes: An investigation of concurrent validity in elementary school. *The California School Psychologist*, *14*, 81-88.

Rural Health Information Hub. (n.d.). Retrieved December 10, 2017, from https://www.ruralhealthinfo.org/states/georgia

Rusby, J. C., et al. (2007). "A descriptive study of school discipline referrals in first grade." Psychology in the Schools 44(4): 333-350.

Sugai, G., et al. (2000). "Preventing school violence: The use of office discipline referrals to assess and monitor school-wide discipline interventions." Journal of Emotional and Behavioral Disorders 8(2): 94-101.

Spaulding, S. A. Irvin, L. K,, Horner, R. H,, May, S. L., Emeldi, M,, Tobin, T. J., & Sugai, G. (2010). Schoolwide social-behavioral climate, student problem behavior, and related administrative decisions: Empirical patterns from 1,510 schools nationwide. *Journal of Positive Behavior Interventions, 12,* 69-85. doi: 10.1177/1098300708329011

Tobin, T. J., & Sugai, G. M. (1999). Using sixth-grade school records to predict school violence, chronic discipline problems, and high school outcomes. *Journal of Emotional and Behavioral Disorders, 7,* 40-53. doi: 10.1177/10634266900700105 – (Tobin and Sugai, 1999)

Walker, H. M., & Severson, H. (1992). *Systematic Screening for Behavior Disorders: Technical manual.* Longmont, CO: Sopris West.

Walker, H. M., Severson, H. H., & Feil, E. G. (1995). The Early Screening Project: A proven child-find process. Longmont, CO: Sopris West.

Walker, H. M., Severson, H. H., & Feil, E. G. (2014). Systematic Screening for Behavior Disorders (SSBD) technical manual: Universal screening for PreK–9 (2nd ed.). Eugene, OR: Pacific Northwest Publishing.

Weist, M. D., Rubin, M., Moore, E., Adelsheim, S., & Wrobel, G. (2007). Mental Health Screening in Schools. *Journal of School Health, 77*(2), 53-58. doi:10.1111/j.1746-1561.2007.00167.x